Opportunistic Method for Road Surface Noise Labelling: Data Cleaning

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ABSTRACT

Road surface type and degradation contribute significantly to the rolling noise emission. In recent times, due to the innovation in vehicle propulsion, rolling noise also becomes a main factor in noise emission for lower order roads. Monitoring and labelling these roads, requires considerably more effort than monitoring primary roads and highways due to their large number. Therefore, we propose an opportunistic method where vehicles that are on the roads for other purposes, are used for rolling noise monitoring. The proposed method may also have some additional benefits over the standard CPX regarding the distribution of tires used and the spread of typical driving speeds. However, measurement conditions are not as well known and may influence the results obtained from individual vehicles significantly. The abundance of measurements data from many vehicles will nevertheless allow to eliminate any modifiers and confounders. To that end, a machine learning cleaning algorithm inspired by denoising auto-encoders has been designed and implemented. This cleaning algorithm improves the convergence of measurements, giving the same quality of measurements with a lower number of passages and cars on a road segment.

1. INTRODUCTION

Rolling noise is gaining importance in overall road traffic noise emission due to reduced engine noise, in particular for light vehicles. This makes road surface choice and maintenance an important

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noise mitigation strategy in urban areas and on minor roads. It can be expected that local governments increasingly use this opportunity as part of their noise action plans. To monitor the effectiveness of the strategy, but also to steer priorities for maintenance, monitoring of road surfaces is important. This monitoring is preferably automated and requires high spatial and temporal resolution. Today, CPX [1] and to a lesser extend OBSI [2] are a widely used methods for assessing the effect on rolling noise of long stretches of roads. However, for the above purpose, CPX has a few disadvantages. Firstly, it requires dedicated equipment and dedicated driving which implies a significant labor cost. For this reason, this monitoring is often limited to highways and main roads and repeated only yearly and even at a lower time interval. Secondly, a single measurement may be sensitive to occasional situations such as freshly laid surfaces, extreme traffic situations, weather. Since the CPX standard corrects for most of these, repeated measurements differ by less than 1 dB under well-controlled situations [3], but there remain some differences between devices [4]. Thirdly, the standard tire, including the aging correction, may cause some offset [5]. In 2019 [6] we proposed opportunistic sensing as an alternative for monitoring and labelling road surfaces. Opportunistic sensing uses vehicles that are already on the road for other purposes than noise monitoring. This tackles specifically the first issue: obtaining good coverage of roads with a high update frequency. One could argue that also the other two issues regarding CPX are addressed, but thus far no proof has been given. However, there are also some drawbacks to opportunistic sensing. Each measuring device has to use low cost equipment for sensing noise and vibrations and easy installation and robustness are key. By conducting the measurements inside the car, these conditions can easily be met but it causes each individual measurement to be subject to sensor calibration and measurement noise issues. Yet, the abundance of repeated measurements allows to use big data and machine learning techniques to tackle these issues. The underlying manuscript illustrates the denoising auto encoder technique that we have used and the way it improves convergence of the average measurement. More details will be provided in a journal paper

2. METHOD

Details on the practical implementation of the opportunistic sensing can be found in previous reports by our group [6]. For clarity, the relevant parts of the methodology are repeated, with the extension of the methodology related to the denoising autoencoder

2.1. Opportunistic sound and vibration measurements

Roads are measured using sensor boxes installed in the trunks of passenger cars. Tri-axial accelerometer data, 1/3-octave bands and GPS location are recorded by the measurement system. he observations are linked to 20m OpenStreetMap segments, including lane identification using the method presented in [7]. The equipment has been installed in the cars of volunteers mainly living in the Ghent area (Belgium) and measurements were collected during their normal day-to-day activities: travelling for work, leisure and shopping. The amount of data has vastly increased: 7 cars collected data during almost 2 years. Two cars have been deprecated, as their devices produced significant outliers. For development purposes, we have kept the raw audio files which allowed us to explore several sound features. However for the results in this manuscript, only one-second aggregated spectral levels were used. The tyre is an important factor for rolling noise production [5]. Therefore, multiple passages of multiple cars on a road section would be necessary to obtain an accurate picture of the road noisiness.

2.2. Speed correction

It is well known that driving speed has a strong effect on rolling noise. Hence, correcting the measured levels for this should constitute a first step in the data processing. In [6], for each separate car c and frequency band f a Generalized Additive Model (GAM) [8] g has been fit to the 1/3-octave band noise levels L:

$$dL_1(f, i, t, c) = L(f, i, t, c) - g(f, c, v(t)) \tag{1}$$

i is the location of the car (a 20m segment), t is the passage time and $v(t)$ is speed. The training data is the first hours of driving for every car. dL is then a measure of how much the current road segment differs by noise level compared to the average road.

2.3. Cleaning algorithm using a denoising auto encoder

The distribution of roads (i.e. "the average road") could change from driver to driver. Therefore, in case an area is solely measured by one driver, then the measurements could be offset (e.g. appear loud when the average road is silent). Here, a neural network is proposed to transform measurements taken by one car into the virtual measurements taken by another car. This then allows to average over several cars that may or may not have driven on the road segment during the observation period. The layout of the neural network is given in figure 1. This reflects a denoising auto encoder (DAE) structure [10]. Features comprise of: statistical and spectral sound levels, tri-axis acceleration, spectral vertical acceleration (in 1/3-octave bands), speed, spectral texture level [9] and the measurement device (as a binary vector). The features are split up into three sets: sound and vibration input features (IF), context variables (CV) and output sound features (OF). The context variables adjust the conditions which could change from passage to passage: horizontal acceleration, speed, temperature and car identifier. Context variables which describe the input (CV_{in}), are concatenated in the first layer of the neural network. Context variables which describe the output condition (CV_{out}), are only introduced in the bottleneck layer. The features are first speed corrected, as described in equation 1. Training explores the requirement that measurements taken under different conditions and by different cars on the same stretch of road should reflect the same underlying road surface, at least if they are taken within a few months of each other. By using the contextual variables also in the reconstruction step, measurements taken in one context are effectively transformed to another context. In the prediction step, the input feature vector is transformed into output features of every single car at reference conditions ($20°C$, $0m/s^2$ horizontal acceleration, same speed). Then, the prediction is averaged by passage to obtain a single prediction for every passage. An essential condition of this method is a partial spatial overlap between several devices. Therefore, it is hypothesised that the bottleneck layer encodes the noisiness of the road, irrespectively of the measured conditions. If that is the case, then not all the cars need to overlap with each other: only the chain of two-by-two forming the connection of all cars would be sufficient. The DAE-corrected relative noise label is called $dL_2(f, i, t, c)$.

3. RESULTS AND DISCUSSION

The rolling noise label for each 20m road surface is obtained for all 1/3 octave band levels, but the focus is on the 1/3-octave bands within the range 315Hz till 4000 Hz. For the purpose of illustrating the impact of the DAE in this paper, the 800 Hz band is considered as it is at the edge between the spectral region where cracking and stone loss is important and the region where pore filling contributes significantly [13]. In figure 2: for two locations around the city of Ghent (Belgium), the convergence at 800Hz of the DAE training method is shown and compared with the label when only the speed correction of section 2.2 is applied. DAE relative noise levels converge much faster than the speed corrected measurements. In addition, without the DAE, the standard error jumps up, as a consequence of a sudden increase in standard deviation when a new car is introduced to the dataset. This is no longer the case after DAE correction.

Focussing first on the mean measurement at location A. Cars a and c dominate the measurements. DAE correction gives a lower prediction of the noise level. Cars a and e could have sampled on average more silent roads, which results in higher noise level when applying speed correction,

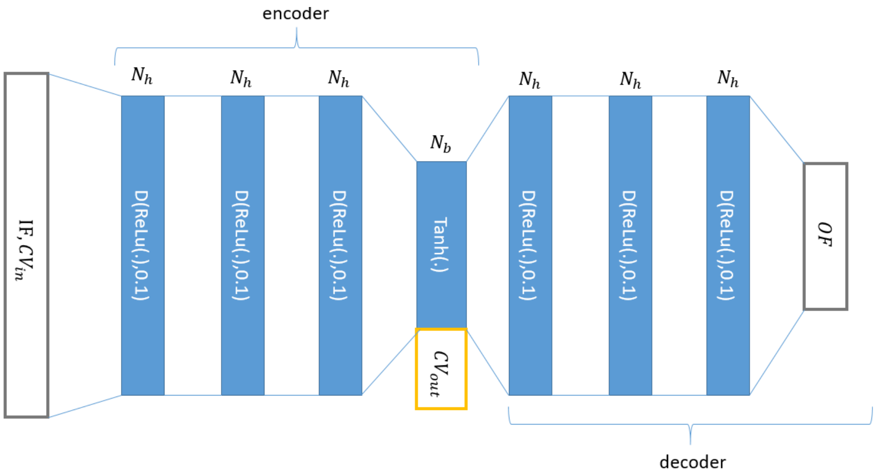

Figure 1: Structure of the denoising auto-encoder (DAE) [10] used to clean measurements. The network is a multilayer, deep neural network. Amount of hidden nodes per layer: N_h = 300 and amount of bottleneck nodes: N_b = 20. Tanh refers to tangens hyperbolicus, ReLu to Rectifier Linear Unit [11] and D to a dropout operation [12].

which assumes the same roads are driven on average. By transforming the measurements to virtual observations by other devices using the DAE and averaging over these, the relative noise level obtained is lower. At the instance when car b, c and d is introduced, the speed corrected noise level drops but does not yet reach the DAE corrected level.

Next, on location B: car b is initially the most prominent car. At around 10 passages, car a is introduced and comprises a large chunk of the observations. Measurements of different cars are introduced at different instances, which affects the distribution of the tyres. Again, speed corrected measurements show to be highly affected by the device which has sampled the location, while DAE corrected measurements reach a final mean level after a couple of observations.

Finally in figure 3, DAE corrected noise levels are plotted in time for 6 locations. The locations at E17 and N60 have been resurfaced respectively in July 2019 and November 2019, which can be seen as a drop in the noise level. The other locations show slightly increasing noise levels over the measurement period. This could be caused by the degradation of the road surface. At location B401, the noise levels are slightly higher in September 2019 and are again lower in November 2019. This finding could be due to a local change in the road. At the start of the measurements and before and after monthly intervals where no data are available, the observation sometimes jumps up or down. This is simply due to the averaging over only a couple of observations. Measurement errors of the order of 0.5 dB are not uncommon even after the DAE correction in case of only one or two observations.

4. CONCLUSIONS

The opportunistic method uses sensor devices placed in the trunks of passenger cars that are on the road for other purposes anyhow, to measure the noisiness of roads. However this approach implies that some modifiers and confounders influence the measurements. To remove the influence of speed, a Generalized Additive Model correction was introduced in [6]. This manuscript shows that average noise levels at a location are very sensitive to changes in the car (or tyre) distribution. A calibration procedure based on the denoising auto-encoders (DAE) has been proposed. The DAE is trained on the assumption that measurements made by different cars should reflect the same underlying road state and relies on a partial overlap of the area which is covered by the different measurement devices. It is shown that DAE-corrected noise levels converge much quicker and they are very stable to the fact of which devices performed the measurements. This ensures that the long term trends can be observed

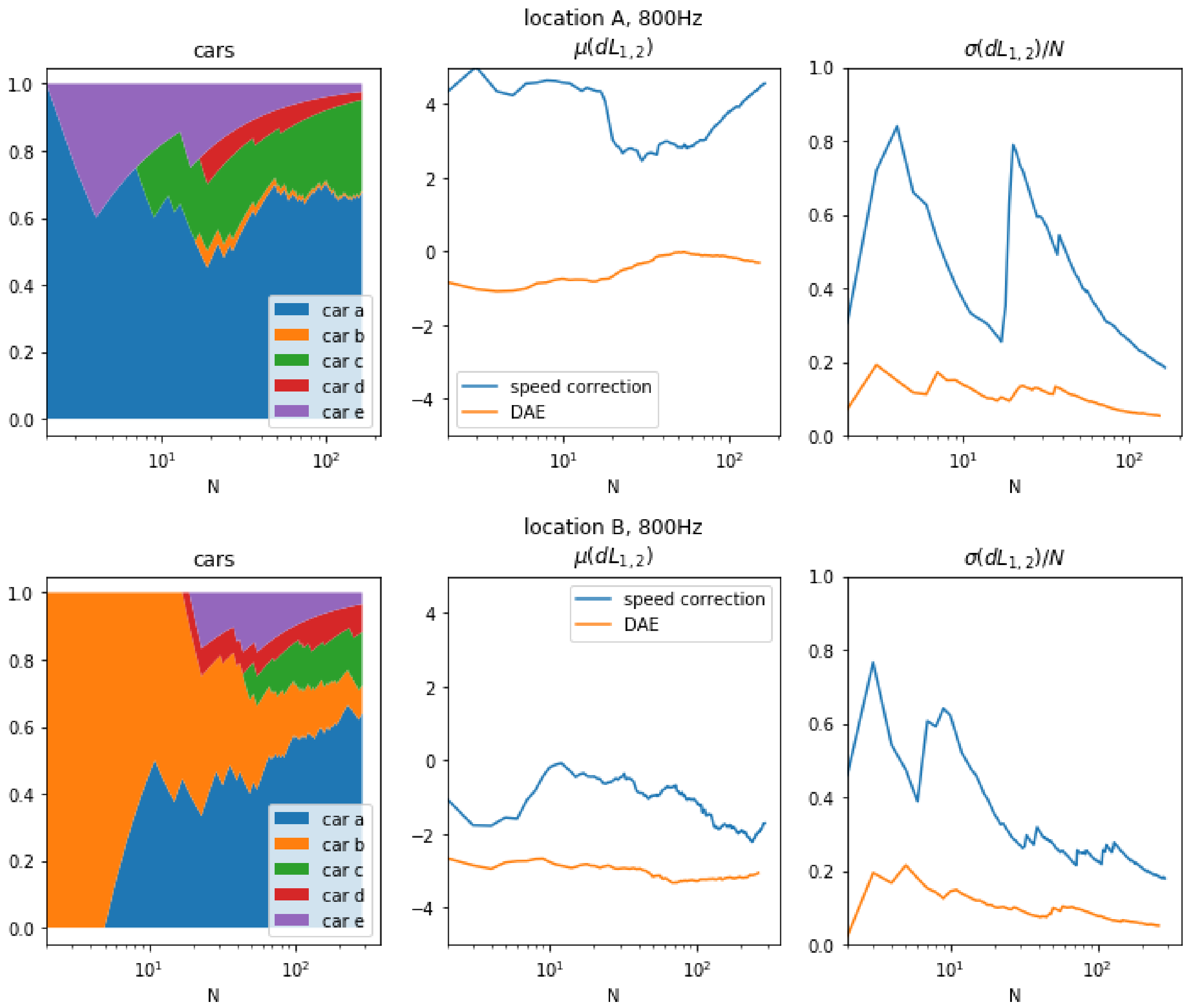

Figure 2: Convergence of DAE cleaning compared to only speed corrected noise levels. N is the amount of passages taken (logarithmic scale). Left: fractional mix of cars, middle: mean value of sample, right: sensor convergence,. Location A: R4, Merelbeke, Belgium (51° 0' 40.5252" N, 3° 44' 28.1256" E). Location B: B401, exit to E17, Gentbrugge, Belgium (51° 1' 12.0894" N, 3° 43' 55.0986" E).

from the DAE noise levels: for instance changes in the road surface due to resurfacing. Although already visible in the presented data, an open research question still remains: how accurate could continuous degradation of roads be detected (e.g. smoothing of the top layer of the asphalt or stone loss).

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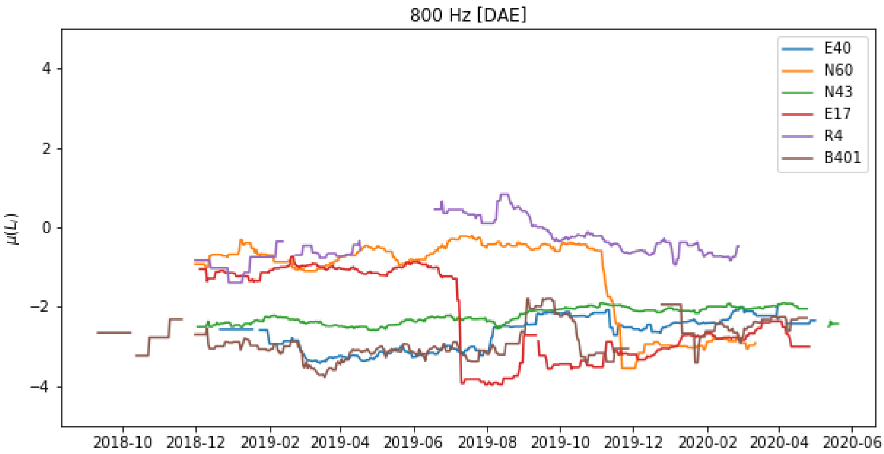

Figure 3: Evolution of the measured DAE noise level during 16 months. For every day of the year a moving average window of 1 month is shown. Locations: ***E40*** *(51° 0' 56.8548"N, 3° 42' 19.1622"E),* ***N60*** *(51° 0' 5.331"N, 3° 41' 30.0474"E),* ***N43*** *(51° 1' 11.892"N, 3° 40' 56.3484"E),* ***E17*** *(51° 2' 46.5534"N, 3° 48' 6.2172"E),* ***R4*** *(51° 0' 40.5252"N, 3° 44' 28.1256"E) and* ***B401*** *(51° 1' 12.0894"N, 3° 43' 55.0986"E)*

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